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A High Precision Reference Data Set for Pedestrian Navigation using Foot-Mounted Inertial Sensors

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***Abstract*— In this paper we present a reference data set that we are making publicly available to the indoor navigation community [8]. This reference data is intended for the analysis and verification of algorithms based on foot mounted inertial sensors. Furthermore, we describe our data collection methodology that is applicable to the analysis of a broad range of indoor navigation approaches. We employ a high precision optical reference system that is traditionally being used in the film industry for human motion capturing and in applications such as analysis of human motion in sports and medical rehabilitation. The data set provides measurements from a six degrees of freedom foot mounted inertial MEMS sensor array, as well as synchronous high resolution data from the optical tracking system providing ground truth for location and orientation. We show the use of this reference data set by comparing the performance of algorithms for an essential part of pedestrian dead reckoning systems for positioning, namely identification of the rest phase during the human gait cycle.**

***Keywords*—Pedestrian Positioning, Inertial Navigation, Human Odometry, Reference Data Set, Optical Tracking System, Motion Capture (mocap), Pedestrian Dead Reckoning (PDR)**

Introduction

Recent years have seen many advances in pedestrian localization in GPS denied environments [1-4]. In particular, work has focused on the sensor fusion approach drawing on measurements from sensors such as accelerometers and gyrometers, barometers, and magnetometers in conjunction with non linear estimation techniques such as particle filtering. An important building block is so-called human odometry or pedestrian dead reckoning (PDR) which tries to estimate the individual steps of a pedestrian while he or she is walking in the environment. Estimates of the steps which are obtained in a relative coordinate system are then combined with other sensor data such as wireless positioning or information such as the building floor plans [2-4]. Foxlin pioneered the use of a Kalman filter and Zero Velocity Updates (ZUPTs) to estimate the step vector from step to step with a very high accuracy, especially in the distance travelled [1, 5]. Critical is the correct identification of the rest phase of the foot from the IMU raw data (accelerometers and gyros). During a ZUPT the integration of the inertial navigation system (INS) is reset and the Kalman filter operating in the INS error domain can estimate some of the IMU error states, significantly reducing the error built up over time.

Figure 1. Photograph of the optical tracking system. The camera on the right was used to make a video recording of each experiment

Experiments have shown that the ZUPT is dependent on conditions such as floor material (soft carpet, tiles, grass,…), shoes (boots, sneakers, high heels,…), as well as type of motion (walking, running,…).

Motivation for the Work

Numerous groups from academia, research and industry are currently investigating the use of foot mounted inertial sensors for human odometry / PDR. The experimental effort that needs to be invested before actual evaluations or data processing can begin is high. Every group needs to acquire the necessary sensors, establish data collection protocols and systems (HW and SW) and then perform the actual measurements. A particular burden is the establishment of reliable reference data. The simplest options are to undertake closed tracks that return to the starting point, follow defined patterns such as circles or rectangles, or adhere to a building layout. While these methods are often sufficient to confirm that the basic data processing is functioning at least superficially, they do not allow researchers to investigate more closely exactly where and how positioning errors occur during the track. Furthermore, it is difficult to verify the performance of high precision human odometry with these methods where one compares the ground truth of the user's location with perhaps 0.5 m accuracy against a PDR algorithm's output. This is compounded with the fact that the sensors are not necessarily co-located on the user's body. To address this problem use an optical reference system that can provide highly accurate reference information (ground truth) about the position and orientation of the actual sensor array.

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Optical Reference System

Our reference system measurement setup consists of a commercial motion capture system (Bonita by Vicon) [12] integrated into our own software framework. We employ a configuration of eight infrared (IR) cameras and strobes that provide a full and redundant coverage of an area measuring approximately 3½ by 6½ meters, within which the experiments are conducted (see Fig. 1). The user equipment, i.e. the shoe with the mounted IMU is tracked with the aid of several firmly attached small IR reflectors.

Figure 2. Photograph of shoe #1 showing the IR reflectors tracked by the optical tracking system. The IMU is firmly attached at the instep of the shoe

After initialization, the tracking system recognizes the tracked user equipment due to the fact that a number of cameras see a sufficient subset of markers at all times. The tracking system processes the camera signals and provides highly accurate measurements of the tracked user equipment in terms of its location and orientation at a rate of about 100 Hz.

We used two arrangements for reflectors on the shoe. Shoe #1 (a right shoe) – used in the majority of experiments – had 7 reflectors on the tip of brass rods firmly attached to its right side, front and back (see Fig. 2). The other two shoes (Shoe #2 and Shoe #3, right and left shoes respectively) had markers attached on their sides and top with tape.

EXPERIMENTAL SCENARIOS

Overview

The resulting reference data is very simple to describe and to use. It consists of time-stamped ground truth data as well as the readings from the IMU and the co-located 3 axis magnetometer. A video accompanies each data set so that a user of the data can associate data portions to individual steps or movement of the subject.

To provide a rich data set we have measured human steps under the following conditions:

1. Different floor surfaces such as carpets and hard floors.
2. Three different shoes worn by three different adults and of both genders (however a majority of the data sets were taken from one of these subjects.
3. A variety of walking modes, such as slow and fast walking, turns, loops, rectangles, rapid direction changes, walking backwards, running, and transitions.
4. In total, 16 experiments were conducted, 13 by Subject #1 of roughly 60 seconds duration each; 2 by Subject #2 (male, Shoe #2, both roughly 300 seconds each) and one by Subject #3 (female, Shoe #3, roughly 300 seconds).

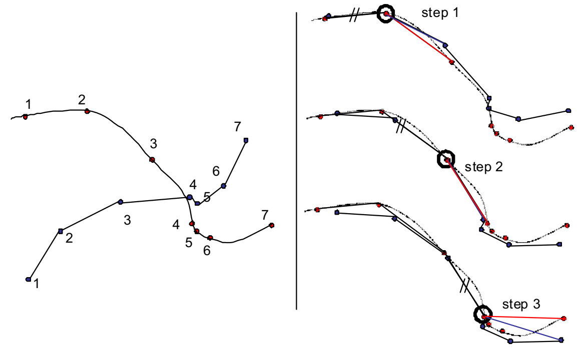

Figure 3. Illustration of our proposed method of per-step error computation between reference data (red, curved lines) and IMU-based odometry (blue, straight lines between points). Left: the two tracks are initially not aligned. Right: At each comparison step we rotate and shift the data so that the two vectors at the *last* step are parallel (//) and compare the current resulting step vectors (short blue and red lines) in length and angle. Steps must be larger than a certain threshold (step 3 ignores data points 4 and 7).

We argue that reference data on short segments of motion that are possible within a room are sufficient to evaluate different algorithms, whenever the ground truth is sufficiently accurate. In this way researchers can concentrate on how their algorithms detect individual phases of the human stride as well as the errors that occur during ZUPT-aided INS processing or other dead-reckoning algorithms. For all of the data sets we also provide results of our own simple ZUPT algorithms and 9-state Extended Kalman filter position estimates for comparison purposes.

At some instances, in particular at the beginning of some experiments, the reference system did not provide data – the user was not in the observation volume (for instance logging was turned on while outside the volume). Such instances are clearly evident from the ground truth reference data (since all entries contain zeros) and do not effect their use to any significant degree. This is because the majority of interesting features such as steps and turns were within the reference system's observation volume. Furthermore, since the reference system provides time stamped absolute position and orientation, omissions only affect a position evaluation at these time instances and not a loss of reference data henceforth.

Time Stamping and Synchronization

Each data set is composed of two data subsets: one from the reference system and the other from the shoe mounted IMU. Since the IMU provided no means of external triggering we had to synchronize its data manually for each experiment. To this aim we included two synchronization events in each experiment (one closer to the beginning and one towards the end) which consisted of a firm and temporally isolated stomp on the ground.

The signature of such an event is so unique that it is possible to identify the time offset between reference system data and IMU data to within one sample (0.01 s). We verified that the evaluation produced the same value for both early and late synchronization events in each experiment. The raw data provided is not corrected (time shifted) but we provide the synchronization (time shift) which we evaluated for each data set (experiment).

List of Experiments

Below we have listed the experiments and their description:

ID	Name	Duration	Subject	Description
1	walk 2D - rectangle	60 sec	Subject #1(male)	Rectangular shape (Shoe #1)
2	walk 2D - rectangle other direction	60 sec	Subject #1(male)	Rectangular shape in opposite direction to ID1 (Shoe #1)
3	walk 2D - straight	60 sec	Subject #1(male)	Straight segments up and down (Shoe #1)
4	walk 2D - 8	60 sec	Subject #1(male)	"8" shaped pattern (Shoe #1)
5	walk 2D – straight fast	60 sec	Subject #1(male)	Straight segments up and down – fast walking (Shoe #1)
6	walk 2D – on table	60 sec	Subject #1(male)	On hard-surfaced table in half circular shape (Shoe #1)
7	run 2D – straight	60 sec	Subject #1(male)	Running straight segments up and down (Shoe #1)
8	run 2D – circle	60 sec	Subject #1(male)	Running in a circular pattern (Shoe #1)
9	run 2D – circle other direction	60 sec	Subject #1(male)	Running a circular pattern in other direction to ID8 (Shoe #1)
10	walk 2D – carpet straight	60 sec	Subject #1(male)	Straight segments up and down on carpet (Shoe #1)
11	walk 2D – carpet only	60 sec	Subject #1(male)	Straight segments up and down without leaving carpet (Shoe #1)
12	run 2D – carpet running	60 sec	Subject #1(male)	Running across carpet (Shoe #1)
13	walk 2D – ID10 carpet shape, no carpet	60 sec	Subject #1(male)	Same shape as ID10, but without carpet (Shoe #1)
14	walk 2D – Patrick long	300 sec	Subject #2(male)	Long walk with different patterns (Shoe #2)
15	walk 2D – Patrick mixed	300 sec	Subject #2(male)	Long mixed walking and running with different patterns (Shoe #2)
16	walk 2D – Mercedes mixed	300 sec	Subject #3 (female)	Long walk with different patterns (Shoe #3)

Data set formats

The data sets are comprised of these files: the IMU data, the reference data and a text description file that includes the time synchronization information.

The data from the IMU (Xsens MTx-28A53G25 [11]) was sampled at 100Hz and is temperature-compensated internally by the device. Our IMU reference data sets follow this simple format:

not_used not_used IMU_timestamp acc_x acc_y acc_z –turnrate_x turnrate_y turnrate_z magnetometer_x magnetometer_y magnetometer_z not_used

Accelerations are in m/s^2, turn rates are in radians/s and the magnetometer readings are in a.u. (arbitrary units) normalized to the earth field strength. The IMU timestamp is in seconds.

The data format of the optical reference system is described in the downloadable files [8].

COORDINATE SYSTEMS

When dealing with inertial navigation one needs to pay close attention to the different coordinate systems that are involved. In this paper we only describe three coordinate systems that are of importance to the data processing: The inertial sensor frame in which we obtain the measurements of the IMU, the navigation frame, and the optical reference system coordinate system. Due to the short duration of our experiments (60 - 300 seconds) we can assume that the tangent plane centered on our location does not rotate significantly within the navigation frame; the small rotation due to the rotation of the earth is assumed to be much smaller than the gyro drift of the low cost MEMS IMU.

We have calibrated the reference system so that the vertical axis (z) is parallel to the gravity vector (plumb line) but with no special constraints as to the orientation with respect to heading within a geodetic reference.

DATA PROCESSING ALGORITHMS

Foxlin [1] introduced a processing chain for pedestrian dead reckoning using foot mounted inertial sensors and additional sensors such as magnetometers and GPS. He employed an Extended Kalman Filter (EKF) operating in the error domain of the strapdown inertial navigation system (INS), and zero velocity pseudo-measurements (ZUPTs) during the stance phase to reduce the error drift to one linear in time. With this approach the distance travelled can be estimated quite accurately but errors significantly affect the heading due to the weak observability of the pertinent gyro error states. This algorithm is now state-of-the art in pedestrian dead reckoning with shoe mounted sensors. The ZUPT can be implemented in many different ways and is a topic of current research (see for instance [7, 9] which compare different approaches for computing the ZUPT during standard walking). Today's algorithms typically draw on short term statistics of the accelerometers, gyros or both, and compare these to predefined thresholds to compute the binary ZUPT signal.

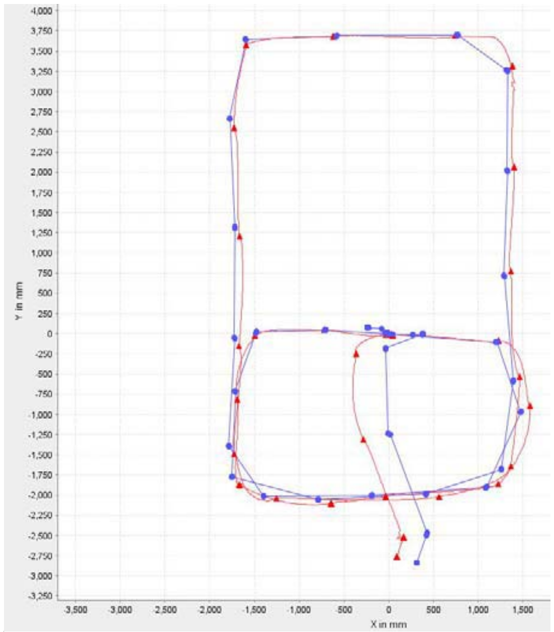

Figure 4. Example of the ZUPT-aided EKF processed walking data set "walk 2D - rectangle other direction" (blue, circles) against the ground truth reference data (red, triangles).

QUANTITATIVE EVALUATION

Error Modelling

In this paper we present a very simple way of comparing the ground truth reference data with the output of the EKF/ZUPT odometry. Since pedestrian odometry is a *relative* positioning method we are interested in comparing the accuracy of computing steps or other short segments of motion in terms of distance travelled and heading change. Although the EKF computes the orientation of the shoe together with its position in the inertial frame we are not so much interested in the orientation, but rather the estimated step vector.

Fig. 3 illustrates a typical situation in 2D. On the left we see the point-wise estimates of the EKF at each ZUPT (blue) connected by straight blue lines. Segments 1-2, 2-3, 3-4, and 6-7 correspond to "normal" human steps and the points in between may be the result of an erroneous ZUPT or a shorter or irregular step. The reference curve shows the ground truth and red points correspond in time to the blue ZUPT points. On the right side of the illustration we show the simple comparison.

We first compute two 2D vectors that are to be compared, one corresponding to the odometry output and one to the reference system. They are constructed by aligning the ZUPT point with the corresponding reference system ground truth point and then by rotating one of the two traces so that the vectors from the previous step are parallel ("//" in the figure). We then simply compare the length difference between the two vectors (= step length error) and the angle between them (= step heading error). In order to avoid comparison of very short vectors we impose the condition that the odometry vector should be longer than a threshold (we chose 0.5m). In the case that it is shorter we simply wait till the next ZUPT point (see step 3 in the example).

It might be argued that leaving out points could favorably bias the evaluation. However, doing this *does not lead us to actually leave out any data* since the step vector that is eventually compared always originates from the end of the *last evaluated* step vector and any error accrued during this time will manifest itself in a length and angle deviation. In our implementation we also take into account missing data in the reference system by using the time-synchronized reference system data that is larger or equal (in timestamp) to the IMU timestamp and only evaluating the error of the step if the two are less than 100 ms apart. After processing the data we can evaluate measures such as the statistics of the angle or length errors, or cumulative measures.

Exemplary Results

Fig. 4 shows an example of the data processed with the ZUPT-aided EKF against the reference data. We have centered the computed odometry and the reference points just after the first synchronization "stomp" and manually rotated the odometry to fit the reference.

For this publication we have chosen two statistical measures for quantitative evaluation: 1) the cumulative angular step error which is calculated by cumulating the individual step heading errors, and 2) the corresponding cumulative step length error. Both cumulative error processes expose characteristic biases (evident as a constant long-term gradient), drifts (local changes in the gradient) and noise. In the case of a white-noise dominated error process the cumulative errors would, of course, follow a first order random walk. For illustration purposes we have investigated four simple ZUPT algorithms with respect to their influence on the odometry accuracy:

- AM1ND which compares the magnitude of the acceleration vector with the magnitude of the gravity vector g and applying a static threshold (if within 1 m/s^2 of g then a ZUPT is declared; used for instance in [6]),
- A3ND which compares the readings of each acceleration sensor individually against the average sensor reading at the beginning of the walk during a stationary period (if *all* three readings are sufficiently close to their average initial readings then a ZUPT is declared, but the threshold is the same for all axes and was 1 m/s^2),

- AM1T3ND which extends AM1ND by additionally requiring that all three turn rates are below individual predefined thresholds, and
- A3T3ND which extends A3ND in a similar way.

In addition, both AM1T3TN and A3T3ND introduce a latency of one sample (1/100 s in our case) and require

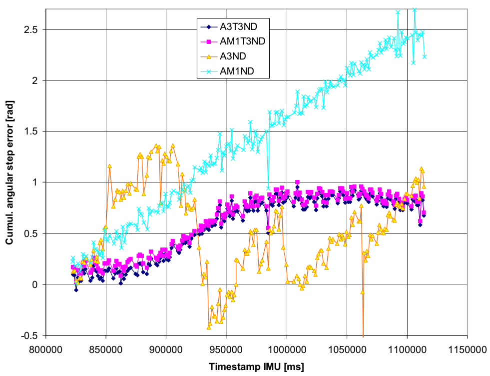

Figure 5. Result of ZUPT aided EKF processing of the walking data set “walk 2D – Mercedes mixed” showing the cumulative heading error for three different ZUPT algorithms.

that a ZUPT be stable until at least the next time step before passing the ZUPT to the EKF. These algorithms also had individual thresholds adapted for all variables.

The ZUPT-aided EKF operated on the INS error space and had 9 states (3 position errors, 3 velocity errors and 3 orientation errors). Our implementation included a scaling factor of 1.03 that lengthens all estimates steps by this factor (is had been optimised heuristically but was not chosen to match this data).

In Figs. 5 to 8 we have plotted the cumulative angular step error, which for any time instance corresponds to the heading error which the estimator exhibits at that time. Data sets “run 2D – circle” and “walk 2D – Patrick mixed” consisted of running and a mixture of walking and running, respectively. The AM1ND ZUPT algorithm was unable to correctly identify the majority of stationary periods during running and hence its error performance was catastrophic during running and has been omitted from the plots. Algorithms AM1T3ND and A3T3ND showed similar performance but we favour the former because it is not sensitive to changes in the orientation of the foot during the stationary period compared to the calibration phase at the start of the walk.

Using the turn rates to detect the ZUPT seems to decrease the variability of the heading error, which will make a later estimation of the heading drift process by a second-tier processing easier. For example, the particle filter in FootSLAM [10] explores the error space of the odometry, and a smaller variability of this error process will improve efficiency and performance. Table 1 shows the distance-travelled error normalized to the total distance travelled. Our ZUPT algorithms using the turn rates also yield better length estimates than the ones using only the accelerations.

TABLE I.
DISTANCE-TRAVELLED ERROR NORMALIZED TO THE TOTAL DISTANCE TRAVELLED FOR A SUBSET OF THE EXPERIMENTS

	ZUPT Algorithm			
Data set	*A3T3ND*	*AM1T3ND*	*A3ND*	*AM1ND*
“walk 2D – Mercedes mixed”	-0.86%	-0.91%	-13.3%	-3.74%
“walk 2D – Patrick mixed”	-1.37%	-2.05%	-11.5%	ZUPT failed during running
“walk 2D - 8”.	-1.93%	-1.94%	-15.5%	-10.3%
“run 2D – circle”	-4.76%	-4.69%	-6.0%	ZUPT failed during running

Obviously, further statistics could be derived in order to investigate the influence of particular characteristics of a step on the error. We have investigated whether the step error is dependent on the step’s duration and angular change.

Questions to be posed here include whether and to which extent the step errors depend on the step’s length, duration, vertical path taken during the stride phase, length and stability of adjoining rest phases, and angular change.

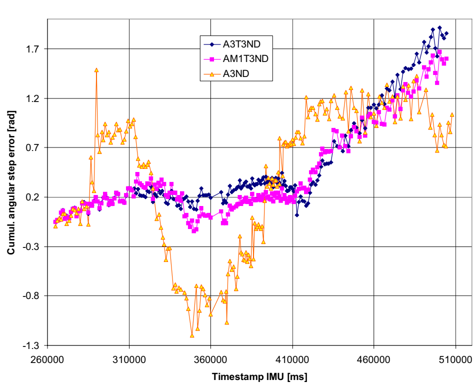

Figure 6. Cumulative heading error of ZUPT aided EKF processing of the mixed running/walking data set “walk 2D – Patrick mixed”.

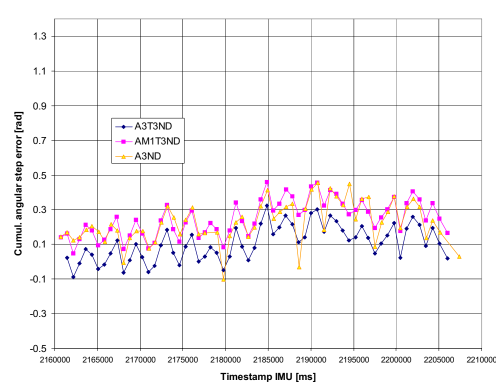

Figure 7. Cumulative heading error of ZUPT aided EKF processing of the running data set “run 2D – circle”.

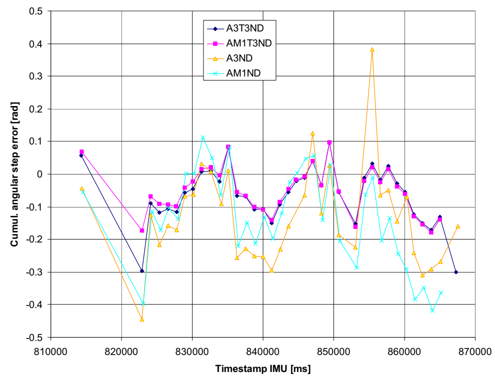

Figure 8. Cumulative heading error of ZUPT aided EKF processing of the data set "walk 2D - 8".

Discussion and Conclusions

In this paper we have presented a methodology for collecting accurately referenced human dead reckoning data sets for use in the design and evaluation of pedestrian positioning systems using inertial sensors. Our data sets have been collected using a foot mounted IMU and are each between one and three minutes in duration and cover a number of different walking styles, surfaces and persons. As a reference system we used a marker-based multi-camera optical tracking system that can pinpoint the pedestrian's shoe to within a millimeter in the designated room-sized tracking volume. We have made the reference data set available on the internet [8] so that others can evaluate their PDR algorithms against the ground truth reference. For comparison, and to illustrate the importance of the zero velocity update (ZUPT) we processed a subset of our data and compared the distance travelled error and cumulative stepwise angular error (heading error). We made the observation that a ZUPT that draws on both the acceleration signals and angular turn rates provides the best performance for both walking and running.

Outlook and Future Work

We have so far only performed analysis of a subset of our data sets in terms of algorithm performance comparisons. More work is needed to thoroughly evaluate all the data and to carefully investigate if conditions exist that systematically contribute to odometry errors.

Future extension of this kind of work could encompass a richer set of subjects, perhaps also including those with a wider range of gaits, such as children, elderly persons or those with disabilities or hindrances (e.g. walking with crutches, limping, carrying a heavy load, or climbing steps). An interesting investigation would be to see whether non-cooperative individuals could be able to manipulate their style of walking to disrupt the odometry or dead reckoning algorithms, by perhaps increasing the time intervals between ZUPTs or making the ZUPT difficult to detect. Furthermore, richer data sets could include more than one sensor array, such as additional IMUs (on the same or on both shoes, hip mounted, handheld, or within a pocket), as well as further sensors such as cameras or laser scanners.

Schemes such as Simultaneous Localization and Mapping (SLAM) based on PDR for pedestrians (e.g. [10]) benefit from improved inertial sensors (which are the focus of recent work, e.g. [5]) as well as from improvements of the signal processing. Furthermore, higher-level estimation algorithms require accurate error models which can be derived from reference data sets. Accurate maps are a vital element for PDR applications in GPS denied environments, and the mapping part of SLAM based on PDR becomes more reliable and more accurate the better the underlying step estimation is. We suggest that quantitative comparative studies be undertaken to compare various forms of PDR in order to better gauge which forms are suited to automated *mapping* and which are perhaps more suitable for widespread *localization* in mapped areas using low cost devices such as a mobile telephone.

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